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## WEIGHT-SPACE MAPPING OF fMRI MOTOR TASKS: EVIDENCE FOR NESTED NEURAL NETWORKS

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### ABSTRACT

In this report, we examine the notion that networks of neocortical activity exist simultaneously across different spatial scales. Our investigations concern human motor data obtained from six motor tasks using functional magnetic resonance imaging (fMRI) at 1.5 T (Sutton et al., 1996). Weights for all pairs of fMRI voxels were calculated across tasks without anatomical bias, and weight maps were produced. We observed regions of interest, which averaged 1 cm<sup>3</sup> in size, and a theoretically predicted network two orders of magnitude larger that linked anatomically related regions together. Temporal analysis revealed the persistence of multilevel clustering through time. Our results support the concept that some dynamic networks in the neocortex are nested within other networks.

### 1. INTRODUCTION

New functional neuroimaging techniques are providing exciting opportunities to study spatiotemporal patterns of brain activity in ways that were unimaginable only a few years ago (Kwong et al., 1992; Ogawa et al., 1992). Spatially localized regions of activity are temporally correlated with behavioral tasks, and there is growing evidence that regions modify with learning (e.g., Karni et al., 1995). There is considerable interest in the temporal course of activity within and between circumscribed regions, which themselves appear to form parts of large distributed brain networks. The similarity in problems faced in trying to understand network dynamics at the scale of neuroimaging data and at the scale of multiple unit recordings is striking.

We are beginning to examine an integration between computational neuroscience and neuroimaging as a means to better understand network organization across large brain regions, especially within the neocortex. Our approach is motivated by an analogy with work on small neural networks and by computational models of nested networks which specifically develop theoretical tools for traversing scales of neural organization. Building upon recent mathematical studies (Sutton and Anderson, 1995), we sought to test the hypothesis that networks of regional brain activity in the neocortex exist simultaneously across different orders of spatial magnitude. We further hypothesized that some networks are nested, and that the detection of such networks is not obvious by standard techniques. In an attempt to identify such functional networks and characterize their organization, we transformed functional images across tasks into a weight-space representation. This approach is similar to the way many small artificial neural networks are constructed.

## 2. METHODS

Human motor data were examined from the performance of six motor tasks using fMRI at 1.5 T (Sutton et al., 1996). The tasks consisted of simple repetitive finger movements, complex alternating finger movements and imagined complex finger movements. Each of these tasks was performed over ten trials for each hand. Each trial lasted 16 seconds and the trials were interspersed with 16 seconds of rest. Data were collected using the T<sub>2</sub>\* BOLD contrast method (Bandettini et al., 1993), with a single-shot, blipped echo-planar imaging sequence (initial flip angle =  $\pi/2$ , TE = 40 ms, TR = 2000 ms). Both static and time-course functional maps were obtained by cross-correlation with a reference function, and time-averaged patterns of activity were generated for each task. Localized regions of interest (ROIs) averaged 1.0 cm<sup>2</sup> x 1.0 cm, with a maximum ROI = 3.5 cm<sup>2</sup> x 1.0 cm. Specific ROIs corresponded anatomically with the behavioral tasks [e.g., M1 activation with contralateral finger movements ( $p < 0.005$ )]. On the basis of signal intensity differences and cross-correlational analysis, there was no objective evidence for large-scale inter-connected networks among the ROIs, either within or between tasks.

Within the conceptual framework of modeling parallel distributed networks, we looked at how the connections among individual voxels represented functions across tasks. In particular, we devised a simple technique for discerning clusters of activity within and between different scales of organization.

For the static case, we considered the six time-averaged activation maps—one for each task. The activation signal was mapped onto:

$$A = \begin{cases} +1 & r > r_\tau \\ 0 & |r| \leq r_\tau \\ -1 & r < -r_\tau \end{cases} \quad (1)$$

where  $r$  is the Pearson cross-correlation co-efficient and  $r_\tau$  is a threshold value. Voxels of varying magnitude of  $r$  above the threshold were dealt with similarly.

For each pair of voxels  $i, j$  within the fMRI slice ( $64 \times 64$  voxels), a weight  $w_{ij}$  was computed by summing the inner products of transformed signal intensity across all tasks:

$$w_{ij} = \sum_{k=1}^N A_i^k A_j^k \quad (2)$$

where  $A$  are the activation values and  $N$  is the number of tasks. Weight maps were produced consisting of lines connecting all pairs of voxels satisfying  $|w_{ij}| \geq w_\tau$ , where  $w_\tau$  was a threshold weight value. No assumptions were made about anatomy or ROIs.

As each task followed a repetitive off-on paradigm with nine usable trials, time-course information was also available. To examine temporal evolution of the maps, the procedure for the static maps was applied to each of the nine off-on trials.

### 3. RESULTS

#### 3.1. Functional Maps

The six time-averaged functional maps revealed complex patterns of activation, including the anticipated ROIs [e.g., primary and supplementary motor cortex, sensory cortex; Bandettini et al. (1993)]. No large-scale networks were apparent at this stage of analysis, nor was any nesting evident.

#### 3.2. Static Weight Maps

$w_\tau=6$

At the highest weight value, a single, tight cluster of connections was observed measuring  $1.0 \text{ cm}^2 \times 1.0 \text{ cm}$ . This corresponded with a ROI in the right S1 (white lines in Figure 1).

$w_\tau=5$

At the next weight threshold, a large, fully-connected network spanning a considerable portion of both hemispheres emerged (black lines in Figure 1), with nodes at bilateral S1 and motor cortex, including the small  $w_\tau=6$  cluster as a node. The lack of symmetry may have been due, in part, to the (mis)-alignment of the head within the scanner. This large network was

approximately two orders of magnitude larger than the  $w_{\tau}=6$  network nested within it (large network  $70 \text{ cm}^2 \times 1.0 \text{ cm}$ ). It was not observed at the higher threshold.

$w_{\tau}=4$

At an even lower weight threshold, the  $w_{\tau}=4$  network (not shown) covered the cortex much more densely, including the ROIs that had been identified from the functional maps. However, the lines at this threshold did not cover the whole cortical slice.

Figure 1: Static Weight Maps. Transverse slice of the human brain at a level through the neocortex. Overlaid upon the anatomical MRI scan, white lines represent connections with  $w_{\tau}=6$  and black lines represent connections with  $w_{\tau}=5$ . The front of the brain appears at the top of the image. As per MRI convention, the left side of the brain is shown on the right side of the image and vice-versa.

### 3.3. Temporally Varying Weight Maps

Weight values in the static and temporal cases differed in their statistical properties, due to the greater temporal averaging in the static relative to the temporal maps. Nevertheless, fully-connected networks were recovered at different spatial scales throughout the course of the experiment. The tasks showed temporal variability within and between scales of organization (Figure 2).

Figure 2: Temporally Varying Weight Maps. Nine images are displayed corresponding to the  $w_{\tau}=6$  weight maps for each of the trials across the six tasks. The time axis refers to the trial number. Each image is oriented the same as in Figure 1, and the outline of the cortical slice appears in grey.

## 4. DISCUSSION

We found weight maps to be an interesting and potentially useful way to visualize patterns of functional brain activity across time and across tasks. The fully-connected nature of the clusters observed at  $w_{\tau}=6$  and  $w_{\tau}=5$  suggests that cohesive networks may mediate related brain functions. The relationship between functional clustering of MRI data and behavior was strongly dependent upon thresholding. In particular, thresholding at higher weight values was tantamount to selecting for more strongly coupled brain regions. Alternatively, one could view weight-value thresholding as a method of drawing cluster boundaries at a specific strength. Even at  $w_{\tau}=4$ , for the static case, no lines were found connecting voxels in the skull or empty space outside the brain where there was considerable noise.

While it is difficult to interpret patterns from the temporal analysis, it was evident that changes in activity were present during repeated task performance. This type of analysis may be helpful in studies of learning and cortical reorganization.

In conclusion, the appearance of functional clustering at distinctly different spatial scales, and the nesting of these clusters, suggests that some motor tasks activate brain regions that are linked by dynamic networks at different scales. One scale consists of discrete ROIs and a second is manifest by networks linking behaviorally related ROIs. Only by looking *across* tasks was it possible to identify these higher-level functional networks. Finally, networks at both scales appeared to have similar properties.

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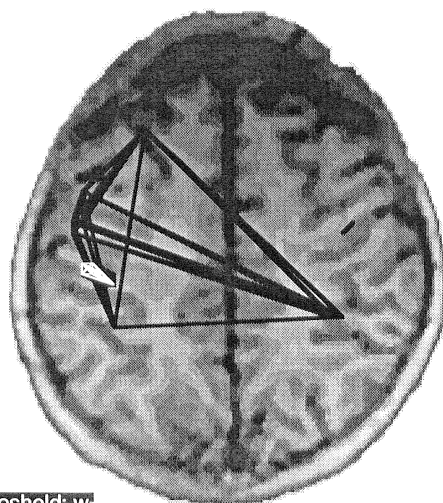
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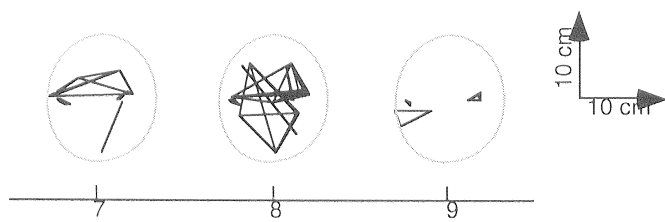
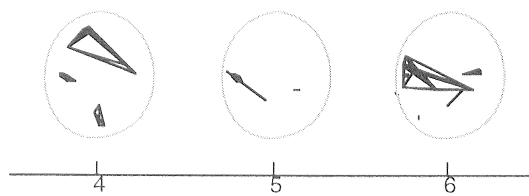
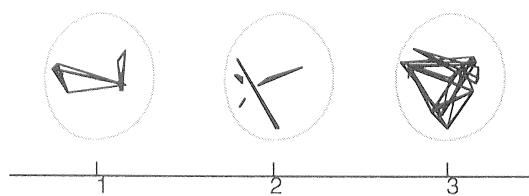
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— threshold:  $w=$   
— threshold:  $w=5$



Trial #  
(32 seconds/trial)

